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Forecasting Youth Unemployment in Malaysia for Ages 15 to 30 Using ARIMA and Prophet Models

Badrul Rahimi[1], Kamil Khalid[1]*

[1] *Department of Mathematics and Statistics, Faculty of Applied Sciences and Technology, UTHM Kampus Cawangan Pagoh, Hab Pendidikan Tinggi Pagoh, KM 1, Jalan Panchor, 84600 Pagoh, Muar, Johor, MALAYSIA.*

*Corresponding Author: kamil@uthm.edu.my
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Abstract

Accurate forecasting of youth unemployment is essential for effective economic planning and policymaking in Malaysia. However, selecting an appropriate forecasting model remains a challenge, particularly when youth unemployment data exhibit relatively stable trends. This study aims to evaluate and compare the forecasting performance of the Autoregressive Integrated Moving Average (ARIMA) model and the Prophet model in predicting youth unemployment in Malaysia. Monthly historical data were analysed using both models, and their performance was assessed on training and testing datasets using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The findings from the testing dataset indicate that the ARIMA (1,1,1) model outperformed the Prophet model, achieving a lower forecasting error with a MAPE of 1.43% compared to 8.92% for Prophet. This suggests that ARIMA provides more accurate forecasts for youth unemployment data characterised by relatively stable trends, while Prophet is more sensitive to complex trend structures that are not prominent in the dataset. In conclusion, the study demonstrates that conventional statistical models such as ARIMA can outperform more recent machine-learning-based approaches when the underlying trends are steady and predictable. The findings provide useful insights for policymakers and government agencies in designing employment programmes and interventions to reduce youth unemployment. Future research may improve forecast accuracy by using longer and higher-frequency datasets, hybrid models, or additional explanatory variables.

1. Introduction

Youth is defined as those who are at a transition phase between childhood and adulthood and covers the physical, psychological, social and economic developments. Youth, according to United Nations, refers to individuals aged 15-24 years [1] though the definition varies in different countries. In Malaysia, the upper age limit of youth is 30, which is legally defined by the age bracketing of youth, the ages between 15 and 30, by the Youth Societies and Youth Development (Amendment) Act 2019 [2]. The paper employs historical monthly data of youth unemployment among people aged between 15 and 30 years in Malaysia. The Department of Statistics Malaysia (DOSM) collects unemployment statistics for citizens between the ages of 15 and 30 through in-person interviews. Only those who are able to work and are not enrolled in school will be included in the data for the 15–17 age group. Based on the self-reported information provided during the interview, the greatest degree of education attained by an individual is used to determine their unemployment status. As a result, the figures represent individuals who are engaged in the employment market but are not enrolled in school or any higher education. [3]

Unemployment is an economic indicator that indicates the status of the labour market and determines the economic growth, distribution of income and social welfare [3]. The fluctuations in the rates of unemployment are influenced by the technological progress, demography, global economic conditions, and governmental policies [4]. According to the previous research, unemployment goes beyond the economic impact, having a profound influence on the mental and emotional state of the individuals, their social condition, and the quality of life [5][6]. In extreme situations, the psychological stress and suicidal thoughts can occur after long periods of unemployment but social support can help alleviate these conditions [7].

Since unemployment is a complex socio-economic phenomenon with a corresponding impact on national development, it is necessary to forecast it accurately [8]. Autoregressive Integrated Moving Average (ARIMA) model by Box and Jenkins is a popular tool of time series analysis and forecasting, as it is applicable in the analysis of patterns observed over time through historical data and is not strongly reliant on assumptions which makes it usable in short-term economic forecasting [9].

Unemployment is a significant economic indicator that can be very crucial in determining job success and motivation policymaking initiatives [10]. Proper forecasting of the unemployment would help the policymakers to develop effective planning. Thus, by including creation of jobs and training on skills, to help contain the adverse impact of unemployment to both the individual and the economy. Moreover, this study assists governments. and enterprises look forward to changes in the labour market and alter fiscal, monetary and investment policies. accordingly. Proactive decision-making and the resilience of the decision is only possible with accurate forecasting regional and national economies. Moreover, an additive time series forecasting methodology, which is an effective forecasting model that is able to capture trend, seasonality, and holiday effects, is called the Prophet model and is created by Facebook which is also strong when it comes to missing data and outliers, which is why the Prophet model is effective in most economic and business forecasting tasks [11].

2. Methodology

The unemployment among the youths in percentages falls between January 2016 and January 2025. The data, which is available in the Department of Statistics Malaysia (DOSM), is separated into training and test data to be utilized in forecasting. The training will last between January 2016 and March 2023, and the testing will last between April 2023 and January 2025. To do the data analysis and develop the model, ARIMA modelling is done using Minitab 22, and the Prophet forecasting model is done using Python. The methods allow a comparative analysis of the forecasting results of ARIMA and Prophet models in forecasting the trend of youth unemployment in Malaysia.

2.1 ARIMA Model

ARIMA is an abbreviation of autoregression process (AR), integration (I), and moving average process (MA). ARIMA is a step applied in Box-Jenkins methodology. Box-Jenkin is the process of finding and approximating models. that involves both AR and MA models. Box-Jenkins needs constant variance and a mean value that is stationary. data. In order to satisfy these requirements before the model identification process, Box-Cox transformation and method of differentiating are used. In the event that the data would not assume a constant variance, the Box-Cox transformation is used and the process is back-transformed to get the expected values. The differencing and determination of whether non-stationary data is transformable to a stationary mean is done by technique.

Model identification, parameter estimation, diagnostic checking, and forecasting are the four primary steps of the Box-Jenkins approach, which are repeated iteratively until an appropriate model is found [15]. For modelling and predicting stationary time series, the non-seasonal Autoregressive Integrated Moving Average (ARIMA) model is commonly applied. The backshift operator is used to express a non-seasonal ARIMA (p,d,q) process as:

$$\phi_p(B)\nabla^d y_t = \theta_q(B)\alpha_t \tag{1}$$

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p, \tag{2}$$

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_p B^q, \tag{3}$$

$$\nabla = \nabla_1 = 1 - B, \tag{4}$$

$$B^j y_t = y_{t-j}, \tag{5}$$

$\phi_p(B) =$ Polynomials in B of order p, (6)
$\theta_q(B) =$ Polynomials in B of order q, (7)
B = Backshift operator, (8)
∇^d = Differencing order – α_t = Random errors. (9)

After the data have been transformed to achieve stationarity, this model describes the present value of a time series as a function of its previous observations and randomised events. The method captures the underlying structure of the series by combining the impacts of unexpected events and historical trends. Once the right orders are chosen, the model may produce accurate forecasts since random mistakes are believed to be independent with constant variance.

Regular differencing can be used to evaluate data that does not show seasonality. Data showing seasonality behaviour can be subjected to seasonal differencing. Once the mean has stabilised, the autocorrelation function (ACF) and partial autocorrelation function (PACF) patterns can be utilised to determine the preliminary models. Table 1 displays the model identification criteria.

Table 1 Identification of ARIMA model

ACF	PACF	Model
Decay to zero with exponential pattern	Cuts off after lag p	AR (p)
Cuts off after lag q	Decay to zero with exponential pattern	MA (q)
Decay to zero with exponential pattern	Decay to zero with exponential pattern	ARIMA (p, q)
Cuts off after lag q	Cuts off after lag p	AR (p) or MA (q)

Table 1 shows the generally common patterns of the autocorrelation function (ACF) and partial autocorrelation function (PACF) as applied in the stage of identification of the Box-Jenkins methodology. A gradual exponential decay of the ACF with a sharp cutoff of PACF also suggests an order p autoregressive model [AR(p)]. Conversely, when the ACF drops at lag q and the PACF is characterized by a gradual exponential drop, a moving average model of order q [MA(q)] should be proposed. A mixed ARIMA model is said to be suitable when the ACF and the PACF exhibit gradual exponential decay. Where both functions die off after a certain number of lags, the underlying process can be either as an AR(p) or MA(q) model, and additional diagnostic analysis is needed to select the most appropriate model specification.

The next step is to approximate the p-value as a reference in order to determine the parameter values of the selected model types. The p-value of the estimated value of the parameter should be less than 5% which implies that the estimated. The value of the parameter is significant. Model checking comes next. To find out, the Ljung-Box test is used. The lack of fit of the time series model. Following the fitting of an ARIMA model to the data, the test was applied to time series residuals [16].

After the estimation of the parameters of the chosen ARIMA model, the p-value was used to assess each parameter's significance. When a parameter's p-value is less than 0.05, it is considered statistically significant. Model checking was done to evaluate the suitability of the fitted model when significant parameters were found. The time series residuals were subjected to the Ljung-Box test to determine whether they exhibited white noise behaviour and to find any residual autocorrelation. The model fits the data well and there is no major lack of fit when the Ljung-Box test gives a non-significant result. Before moving on to forecast performance review, only models that passed these diagnostic tests were chosen for additional examination.

2.2 Prophet Model

The approach illustrated how effectively the Prophet model handled complicated time series data with holiday effects, non-linear trends, and seasonality. Trend function $g(t)$, seasonality $s(t)$, holiday effects $h(t)$, and an error term $\varepsilon(t)$ .The components of this time series are modeled by Prophet be seen in the equation shown below:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon t \quad (10)$$

Where:

$$g(t) = \text{the trend} \tag{11}$$

$$s(t) = \text{seasonal component} \tag{12}$$

$$h(t) = \text{holiday effects} \tag{13}$$

$$\varepsilon(t) = \text{error term} \tag{14}$$

The trend component, *g(t),* is a model of the long-term development of the time series. Prophet is a piecewise linear trend model that has automatically computed changepoints, where the rate of growth can vary over time. This allows the model to show structural variations in the data, such as unexpected rises or falls in unemployment that may come about due to economic shocks or policy interventions. This is because the trend component is flexible and allows Prophet to comply with non-linear trends without overfitting.

The seasonal component, *s(t)* is the cyclic variation that is repeated after a certain time period, for example monthly or yearly. Prophet models seasonality as represented by Fourier series, which provides flexibility of representation as well as the ability to visually smooth repeating patterns. The model adopts this method to deal with the complex seasonal behaviour without necessarily having the data to adhere to a specific seasonal index. Seasonality could occur in the case of unemployment data because of the academic cycles, graduation, or the patterns of entry to labour markets.

The holiday factor, *h(t)* includes the effects of special occasions or holidays that can lead to the temporary changes in the time series. The modelling of these effects is done based on indicator variables that specify happenings and how these might affect a given window of time. In economic time series, the concept of holiday effects can be of use when the events like public holidays, policy announcements, or economic disturbances can affect unemployment rates inconsistent with the trends and seasonal effects.

The error term, *ε(t)* is the random noise or the unaccounted variation in the data, which cannot be accounted by the trend, seasonality or holiday factors. As a general assumption it is normally distributed with a mean of zero. This element is associated with random deviations of real-life data.

The Prophet model is a time series that involves the combination of various essential elements characterizing various patterns in the data. The trend component indicates the general trend of the series and indicates whether the values are increasing, decreasing or not. The seasonal part encompasses recurring and repetitive disturbances that happen at predetermined intervals e.g. monthly or annual variations. The holiday aspect captures the effect of special events or holidays which can introduce the sudden alteration of the data, not of the regular trend or seasonality. Lastly, the error term is the random changes or noise which cannot be described by the other components. The Prophet model can manipulate complex patterns and can give flexible and reliable predictions by splitting the time series into these components.[17]

2.3 Forecast Performance Evaluation

Benchmarking is applied by comparing the model performance in terms of the error measures like RMSE, MAE, and MAPE to determine the best model in time series forecasting. In the ARIMA case, benchmarking usually involves the choice of the best (*p,d,q*) parameters based on information criteria, including AIC or BIC, a test of whether the residuals are white noise, and transformations to stabilise the variance [11]. The Prophet model on the other hand is a model that is used in automated forecasting where the trend and seasonality components are high and its performance can be enhanced by tuning the parameters and cross-validation to minimize overfitting [12].

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_t - \hat{y}_t)^2}{n}} \tag{14}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|y_t - \hat{y}_t|}{n} \tag{15}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|y_t - \hat{y}_t|}{y_t} \tag{16}$$

where:

y_t = The actual value at time t.

$\hat{y}_t$ = The forecast value at time t.

n = Sample size.

Formula above gives the forecast accuracy measures to be used in assessing the performance of the time series models in this study. Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Mean Absolute Percentage Error (MAPE) as represented in Equations (14), (15) and (16) respectively. These measures of errors are used to measure the difference between the actual values, y_t and the values that correspond to the forecasts, $\hat{y}_t$, over a sample size of n observations. RMSE quantifies the square root of the mean of the squared forecast errors and emphasizes more heavily those errors that were larger as a result of the process of squaring. Consequently, RMSE is more sensitive to big deviations and is applicable in cases where one wants to detect models that have a few but significant errors in forecasting. If the value of RMSE is low, the overall forecasting performance is good. MAE is the mean of the absolute values of differences between the forecasted and actual values.

In contrast to RMSE, MAE does not place more emphasis on large errors than on small ones and thus is a simple and easily understandable metric of average forecasting accuracy. The smaller values of MAE reflect on forecasts which on average are nearer to the actual observations. MAPE has forecast errors in the form of a percentage of the actual values and this is used to make comparisons of the performances of different models on various scales. This is done to give an intuitive understanding of the forecast accuracy in percentage terms with a lower MAPE value giving greater predictive accuracy. However, MAPE is sensitive in cases where actual values are near to zero. All in all, these accuracy measures are quite complete as they measure the magnitude and the relative scale of forecasting errors. The models which have low RMSE, MAE and MAPE values are said to have better forecasting ability.

Table 2 Benchmarking of Forecast Performance Evaluation

Method	Best Condition	RMSE	MAE	MAPE
ARIMA	- Choose the best (p, d, q) using AIC or BIC -Ensure residuals are white noise (Ljung-Box test) - Use log transform if the variance is unstable	0.058 – 0.2	0.05 – 0.15	2% – 6%
Prophet	- Adjust the changepoint and seasonality settings - Use cross-validation	0.3 – 0.5	0.1 – 0.3	3% – 10%

Table 2 gives a summary of the conditions of the benchmarks and the common error limits that are applied in testing the ARIMA and Prophet forecasting models. In the case of ARIMA, the best performance is usually attained by ensuring the correct choice of autoregressive, differencing, and moving average orders based on information criteria like AIC or BIC, where the residual of the model is white noise, and where there is instability in the variance which can be addressed by data transformations. In such cases, the ARIMA models usually give RMSE of between 0.058 and 0.2, MAE of between 0.05 and 0.15 and MAPE of between 2 and 6%. In application to the Prophet method, tuning is determined by smart manipulation of changepoint flexibility and seasonality components, and tuning is done by cross-validation. Prophet normally provides RMSE of between 0.3 -0.5, MAE of 0.1 -0.3 and MAPE between 3% and 10% when optimally configured.

3. Result and Discussion

This section presents the results of the analysis and discusses the key findings. The results are interpreted to explain the main patterns observed in the data and their relevance to the objectives of the study.

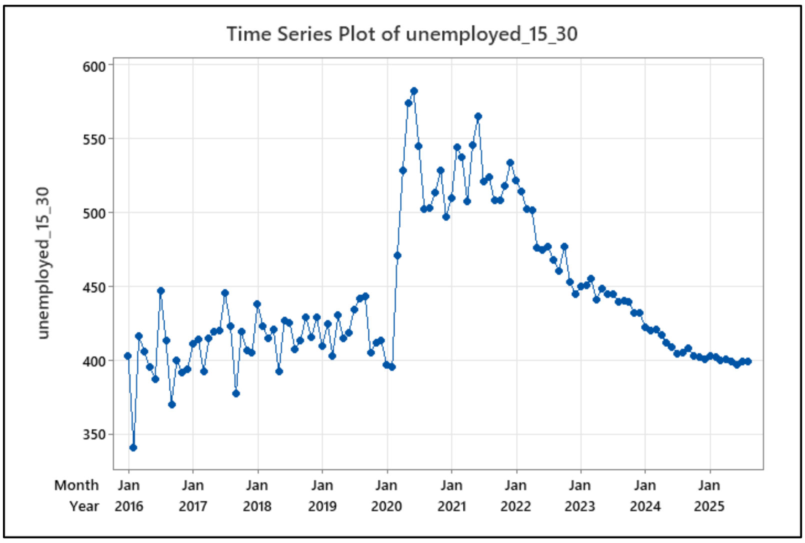

Fig. 1 Time Series Plot of Youth Unemployed for Ages (15 to 30) in Malaysia

Based on Fig. 1, the unemployment trend for individuals aged 15 to 30 from 2016 to 2025 is shown in the time series plot. The unemployment rate experienced only slight changes between 2016 and 2019, with small year-to-year variations, suggesting overall stability during this period. In early 2020, a significant spike occurred, peaking between 2020 and 2021, likely due to the COVID-19 pandemic. Following that, the unemployment rate began to gradually decline and stabilised in 2024 to 2025. Overall, the average level and pattern shift with time, showing different patterns and fluctuations rather than being constant, indicating that the data is not declining.

Table 3 Table of Model Summary

DF	SS	MS	MSD	AICC	AIC	BIC
84	0.356349	0.0042422	0.0041436	-221.179	-221.472	-214.109

MS = variance of the white noise series

The model summary presents diagnostic statistics that evaluate the adequacy of the fitted ARIMA (1,1,1) model. The variance of the white noise series (MS) is 0.0042, indicating relatively low unexplained variation in the residuals. The AICc, AIC, and BIC values are -221.179, -221.472, and -214.109, respectively, suggesting a good model fit, as lower information criterion values indicate better performance. Overall, these results demonstrate that the ARIMA (1,1,1) model provides an appropriate representation of the underlying pattern in the transformed and differenced training data.

Table 4 Prophet Model Forecasting Performance

Method	**Training set**			**Testing Set**		
	MAE	MAPE	RMSE	MAE	MAPE	RMSE
Prophet Model (with normalization)	0.0539	5.4	0.0647	0.0886	8.92	0.0938
Prophet Model (without normalization)	24.34	5.4	30.40	37.16	8.9	39.35

Table 4 shows that the Prophet model performs well in forecasting the Unemployed_15_30 dataset. On both the training and testing sets, the model consistently produces low error values, with RMSE, MAE, and MAPE falling below acceptable thresholds. Specifically, the testing set findings exhibit decreased RMSE (16.76) and MAPE (3.56%), suggesting less overfitting and strong generalisation capacity through ensuring that the error metrics are scale-independent, normalised RMSE and MAE enable fair comparisons between models and intelligible interpretation. Furthermore, good prediction accuracy with relation to the actual data is indicated by MAPE values less than 5%. Overall, these findings support the Prophet model's suitability for short-term forecasting and decision-making as well as its accuracy and dependability in identifying unemployment patterns among people in the 15–30 age range.

The forecasting performance of the ARIMA and Prophet models is discussed and results are shown in this section. On both the training and testing datasets, the models are assessed using three popular error metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). Table 3 summarises the metrics used to compare each model's precision as well as reliability in forecasting trends in unemployment

Table 5 Table of Forecast Performance of ARIMA Model and Prophet Model

Forecasting Method	**Training Set**			**Testing Set**		
	MAE	MAPE	RMSE	MAE	MAPE	RMSE
ARIMA (1,1,1)	0.0468	1.0161	0.0644	0.0652	1.4348	0.0720
Prophet Models	0.0539	5.634	0.0674	0.0886	8.92	0.0938

Table 5 shows the ARIMA model performed slightly better on both the training and testing sets. On the training set, ARIMA had an MAE of 0.0468, an RMSE of 0.0644, and a MAPE of 1.0161%, showing that it fit the historical data closely. Prophet had slightly higher errors on the training set, with an MAE of 0.0539, RMSE of 0.0674, and MAPE of 5.634%. On the testing set, ARIMA also showed lower errors, with an MAE of 0.0652, RMSE of 0.0720, and MAPE of 1.4348%, while Prophet's errors were higher, with an MAE of 0.0886, RMSE of 0.0938, and MAPE of 8.92%. This indicates that ARIMA fits both the training and testing data more accurately than Prophet for this dataset. Overall, ARIMA appears to be more reliable for forecasting in this case, as it produces smaller errors on both historical and new data, while Prophet shows larger deviations.

The ARIMA model is clearly better than the Prophet model based on the error levels of the training and testing sets. In terms of MAE, MAPE, and RMSE, ARIMA is less accurate in both stages, which means that its predictions are closer to the real unemployment figures. One of the logical reasons for this is that ARIMA works very well with data that has a steady trend and little seasonality, which is the situation with the unemployment data utilised in this study. In the meantime, the prophet is supposed to identify complex patterns and significant seasonal trends that are not particularly noticeable in this data. As a result, the prophet produces more significant mistakes and inaccurate predictions. Therefore, ARIMA is a more suitable and reliable model to predict youth unemployment in this situation.

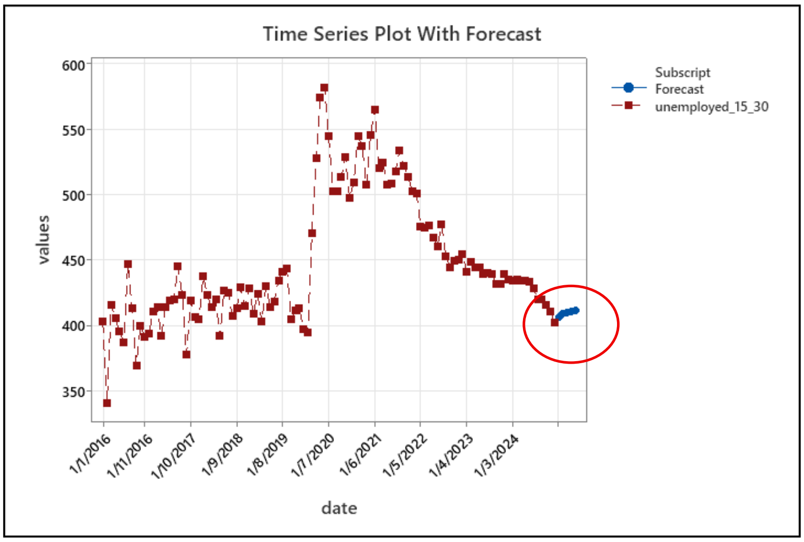

Fig. 2 Actual Time Series Plot of Best Model of Youth Unemployed for Ages (15 to 30) in Malaysia On ARIMA Method

The time series plot in Fig. 2 indicates the past values of ages 15 to 30 unemployment between the years 2016 and early 2025 as well as the forecast of the ARIMA(1,1,1), indicating the next few months. On the whole, the data is subject to shifts in time, as it has some relatively stable time windows and slow trends.

The item that stands out in the chart is the peak in the middle of 2020, when unemployment rates increased significantly. This spike must have been associated with an outside factor triggering a sharp increase in unemployment, including the COVID-19 pandemic, which struck the world with a considerable number of job losses. Following this spike, the values slowly dropped indicating a recovery trend in later years.

The ARIMA(1,1,1) model has been able to describe the trend and variation of the data as a whole. The forecast values, which is depicted in blue at the end of the series, show that unemployment is predicted to stabilize at the end of the next few months at a slightly higher level of 400, which implies that there will not be any drastic changes in terms of high and low levels of unemployment. The forecast line is not jagged, indicating that the model makes a forecast based on the slow trend that was observed in the end of the history data.

Overall, the ARIMA(1,1,1) model fits the historical data both in its ability to accommodate the excessively high figure in 2020 and the ability to make a decent forecast that suggests a steady level of unemployment in the near future.

Table 6 Table of Forecast of future value of unemployed ages (15 to 30)

Date	Forecast value of unemployed ages (15 to 30)
1/2/2025	406.661
1/3/2025	409.018
1/4/2025	410.322
1/5/2025	411.044
1/6/2025	411.443

Table 6 indicates the predicted values of the unemployed youths between the ages of 15 and 30 years in the coming five months with the help of the chosen most efficient model. The findings show that the number of unemployed youths is expected to gradually and steadily rise between February 2025 and June 2025. The projected values increase gradually with an upward trend of 406.661 in February 2025 to 411.443 in June 2025 and indicate consistency. This trend would represent the capacity of this model to embrace the underlying structure and stability in the historical data. The ARIMA model was chosen in final forecasting as compared to the Prophet model because it performed better during model evaluation especially in dealing with relatively stable and predictable trends. Consequently, the ARIMA-based projections present a credible short-term projection on the youth unemployment that can be used to support the planning and decision-making involving the employment policies and workforce programmes.

4. Conclusions and Recommendation

This study compared the effectiveness of ARIMA and Prophet models under labour market uncertainty and economic fluctuation in order to solve Malaysia's lack of precise youth-specific unemployment predictions. The findings demonstrate that the ARIMA (1,1,1) model fared better than the Prophet model in addressing the issue of restricted forecasting tools for young unemployment, generating reduced MAE, RMSE, and MAPE values while successfully capturing the underlying patterns of youth unemployment data. These results show that when youth unemployment trends are somewhat predictable and structurally stable, classical statistical models can produce more accurate forecasts, despite growing interest in machine-learning-based alternatives.

The ARIMA model directly assists policymakers, educators, and labour market planners in creating focused interventions, enhancing workforce allocation, and reacting proactively to shocks like advances in technology and economic crises, such as the COVID-19 pandemic, by providing more precise and reliable forecasts. As a result, this study helps close the forecasting gap mentioned in the problem statement and offers an evidence-based tool for making well-informed decisions on teenage unemployment in Malaysia. By adding hybrid models or other economic and social elements that affect the dynamics of young employment, future study may improve predicting accuracy even more.

This study is limited by its reliance on historical youth unemployment data, exclusion of external factors (e.g., economic growth, policy changes), and analysis of only two models (ARIMA and Prophet). Future research should incorporate additional explanatory variables, explore alternative or hybrid forecasting models, and use longer or higher-frequency datasets to improve accuracy and better support economic planning and policymaking.

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Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The authors confirm contribution to the paper as follows: ***study conception and design:*** *Badrul Rahimi Badrul Hisham;* ***data collection:*** *Badrul Rahimi Badrul Hisham;* ***analysis and interpretation of results:*** *Badrul Rahimi Badrul Hisham, Kamil Khalid;* ***draft manuscript preparation:*** *Badrul Rahimi, Kamil Khalid. All authors reviewed the results and approved the final version of the manuscript.*

References

[1] Department of Economic and Social Affairs| United Nations For Youth. (n.d.). https://www.un.org/development/desa/youth/what-we-do/faq.html
[2] Parliament of Malaysia. (2019). *Youth Societies and Youth Development (Amendment)*.
[3] Department of Statistics Malaysia, 2026. Labour Force Survey. OpenDOSM. https://open.dosm.gov.my/publications/technical-notes/lfs-technotes.
[4] Pohlan, L. (2024). Unemployment's long shadow: the persistent impact on social exclusion. *Journal for Labour Market Research*, *58*(1). https://doi.org/10.1186/s12651-024-00369-8
[5] International Labour Organization (2021)
[6] Bajenescu, T. I. (2022). Why we have unemployment? *Journal of Social Sciences*, *V*(1), 66–72. https://doi.org/10.52326/jss.utm.2022.5(1).08
[7] Jabbar, H., & Fatima, A. (2024). The psychological impact of unemployment on individuals. *International Journal of Innovative Science and Research Technology (IJISRT)*, 2917–2922. https://doi.org/10.38124/ijisrt/ijisrt24jul1699
[8] Hussenoeder, F. S., Koschig, M., Conrad, I., Pabst, A., Gatzsche, K., Bieler, L., Alberti, M., Stengler, K., & Riedel-Heller, S. G. (2024). Psychological symptoms and loneliness in unemployed people diagnosed with mental illnesses. *Social Psychiatry and Psychiatric Epidemiology*, *60*(6), 1437–1443. https://doi.org/10.1007/s00127-024-02806-y
[9] Luo, Z., Jia, X., Bao, J., Song, Z., Zhu, H., Liu, M., Yang, Y., & Shi, X. (2022). A combined model of SARIMA and Prophet models in forecasting AIDS incidence in Henan Province, China. *International Journal of Environmental Research and Public Health*, *19*(10), 5910. https://doi.org/10.3390/ijerph19105910
[10] [Adebiyi, A. A., Adewumi, A. O., & Ayo, C. K. (2014). Comparison of ARIMA and artificial neural networks models for stock price prediction. *Journal of Applied Mathematics*, *2014*, 1–7. https://doi.org/10.1155/2014/614342
[11] Hyndman, R. J., & Athanasopoulos, G. (2021). *Forecasting: Principles and Practice*.
[12] Taylor, S. J., & Letham, B. (2018). *Forecasting at Scale*.
[13] Wilson, J.H. and Keating, B. (2007). *Business Forecasting with Accompanying Excel-Based ForecastX Software*. 5th Ed. Boston, Mass: McGraw-Hill
[14] Taylor, S. J., &Letham, B. (2017). Forecasting at Scale. *PeerJ Preprints*. https://doi.org/10.7287/peerj.preprints.3190v1
[15] GeeksforGeeks. (2025, July 23). *BoxJenkins Methodology for ARIMA Models* GeeksforGeeks. https://www.geeksforgeeks.org/machine-learning/box-jenkins-methodology-for-arima-models/?utm_source=chatgpt.com
[16] Tsoku, J. T., Metsileng, D., & Botlhoko, T. (2024). A hybrid of Box-Jenkins ARIMA model and neural networks for forecasting South African crude oil prices. *International Journal of Financial Studies*, *12*(4), 118. https://doi.org/10.3390/ijfs12040118
[17] Oo, Z. Z., & Phyu, S. (2020). Time series prediction based on Facebook Prophet: A case study, Temperature forecasting in Myintkyina. *International Journal of Applied Mathematics Electronics and Computers*, *8*(4), 263–267. https://doi.org/10.18100/ijamec.816894